Testing a commercial BCI device for in-vehicle interfaces evaluation: a simulator and real-world driving study

Anonymized for review

Abstract

This study is assessing the sensitivity of an affordable BCI device in the context of driver distraction in both low-fidelity simulator and real-world driving environments. Twenty-three participants performed a car following task while using a smartphone application involving a range of generic smartphone widgets. On the first hand, the results demonstrated that secondary task completion time is a fairly robust metric as it is sensitive to user-interfaces style while being consistent between the two driving environments. On the second hand, while the BCI attention level metric was not sensitive to the different user-interfaces, we found it to be significantly higher in the real-driving environment than in the simulated one, which reproduces findings obtained with medical-grade sensors.

Keywords: Driving simulator; Real driving; Distraction; Dual-task; Mental workload; BCI.

Introduction

Multitasking is a commonly observed behavior in everyday life Salvucci and Taatgen (2010). In some circumstances, such as driving, executing concurrent tasks (such as interacting with displays), may impair driving safety Cooper and Zheng (2002); Horrey and Wickens (2004); Rudin-Brown et al. (2013); Törnros and Bolling (2005). Although the use of digital media in cars such as connected apps, navigation systems or music players can be beneficial, they raise issues concerning the design and evaluation of such innovative services.

One major challenge in the domain of in-vehicle infotainment systems concerns evaluation methods Green (2004). While a thorough evaluation is required for near-market innovations, early Human-Computer Interaction (HCI) studies need more agile means of evaluating new concepts. In these situations a low-fidelity simulator might be suitable Jamson and Jamson (2010). While driving simulator measurements can demonstrate adverse effect of a secondary task on driving performance, they will provide little insight into covert attentional phenomenon. For instance, estimating driver's covert attentional phenomenon may require very specific and expensive equipment Mehler et al. (2012); Pomplun and Sunkara (2003); Girouard et al. (2010).

In this context, commercial Brain-Computer Interfaces (BCI) are particularly relevant (i.e., as opposed to medical-grade sensors). Indeed, they could allow for an affordable and easy-to-use way to assess driver attention while multitasking. However, there is a lack of knowledge concerning the potential added value of such devices in human factor research notably in different driving environments (i.e., driving simulator and real-driving testing).

In this work, we test the sensitivity of a commercial and affordable BCI (MindCap XL[1]) relative to two experimental factors: (i) the driving environment that could be either a low-fidelity simulator or a real-driving environment; and (ii) a range of generic user-interface widgets for a smartphone-based secondary task. Participants performed the same car following task in both driving environments while they were interacting with the smartphone application. Application usage, driving speed and BCI metric (so-called attention level) were collected and analysed across the different conditions.

Related Work

Comparison of simulated and real driving

The usage of driving simulators raises the question of transferring the results from simulated (whether of a low or a high quality) to real environments. Several studies found differences between those conditions: Indeed, Reymond et al. (2001) found that in driving simulator experiments curvilinear speed was underestimated when taking a curve. It has also been demonstrated Boer et al. (2000) that participants braked later and stronger in driving simulator than in a real-driving environment. However, Panerai et al.

[1] http://www.mindtecstore.com/en/mindcap-xl

(2001) showed that speed control did not vary significantly between the two types of environments. Finally, Engström et al. (2005) found the estimated workload higher in real-driving condition than in simulated one.

Comparing low- and high-fidelity simulators

Driving simulators exist in a wide range of complexity and fidelity with regard to real-life driving (motion simulation, 3D engine, cockpit etc.) The fidelity of a driving simulator has been shown to have an impact on the way participants react to the virtual traffic events. Indeed, low-cost simulators decrease accuracy in the perception of ego-motion, speeds and distances, which in turn leads to under-estimated inter-vehicular judgements Kemeny and Panerai (2003). The same authors also pointed out that while high-fidelity simulators are required for assessing complex driving situations, low-cost simulators could be used successfully for dashboard ergonomic and simple driving scenarios. Other authors also pointed to low-cost simulator being particularly useful in early prototyping stages of innovative infotainment services Green (2004). For instance, in Jamson and Jamson (2010) authors found consistent measurements across simulator types at least for metrics concerning speed control and secondary task completion time.

Mobile devices and visual-manual distraction

Studies confirm that the increased use of mobile phones while driving degrades driving performance Cooper and Zheng (2002); Horrey and Wickens (2004); Rudin-Brown et al. (2013); Törnros and Bolling (2005). The reason being when one shifts their visual attention to a mobile phone, this leads to visual-manual distraction. Visual-manual distraction refers to any secondary activity that involves controlling hand gestures toward a visual interface. Engaging in such activity will lead to longer and more frequent glances off-the-road Burns et al. (2010). With a high penetration on mainstream market, touch-screen interactions such as those used on current smartphones are both familiar and easy-to-use due to the imprecise interactions required in finger pointing activity. However many studies showed that the type of widget used for a smartphone application impact differently driver's distraction Kim and Song (2014); Louveton et al. (2016). Additionally, it has been shown that text-entry and kinetic scrolling are the two major sources of visual-manual distraction in the car Kujala et al. (2013).

Estimation of mental workload and BCI devices

Mental workload could be estimated by a variety of psycho-physiological measurements such as heart-rate, skin conductance or pupil dilation Collet et al. (2009); Healey et al. (2005); Mehler et al. (2012); Pomplun and Sunkara (2003); Solovey et al. (2014). Another possibility is to use brain activity as input for estimation Fort et al. (2010); Lei and Roetting (2011); Kincses et al. (2008); Liang et al. (2006); Haufe et al. (2014). However, those measurements can be expensive and difficult to setup or to analyze. With the evolution of several commercial and affordable BCI devices, understanding the signals of the brain on the move has become much easier, faster and cost effective. In this respect, several studies demonstrated successful use of simple BCI devices in the context of interactive applications and workload estimation Girouard et al. (2010); Herff et al. (2013); Afergan et al. (2014).

Methodology

Participants

In total 23 participants took part in this study, including 15 for the simulator set-up and 8 for the real driving condition. The driving simulator sample was composed of 12 males and three females with a mean age of 28 years (SD = 4.08) and they had held their driving license for an average of 8.91 years (SD = 4.7). The real driving set-up was composed of seven males and one female with a mean age of 29 years (SD = 5.18) and they had held their driving license for an average of 7.13 years (SD = 2.8).

The population has been drawn from University staff members and students. Each of the drivers participated in the event had a valid European Union driving license (for at least four years) and a normal or corrected-to-normal vision. All participants agreed and signed an informed consent form before taking part.

Car following task

Participants were to perform a car following task on a test track (see the schema of the track in figure 1, LOCATION MASKED FOR REVIEW), either in real-world or in a driving simulator with a 3D version of this test track. The track was a closed course with no other traffic vehicles than those of the experiment. The task was the same for both environment. All the participants were instructed on the task they needed to perform prior to the experiment starting. Traffic was limited to one lead (i.e., preceding) vehicle going in the same direction driving at a constant speed. The participants were asked to follow the car in front of them at all times and never to overtake it and to maintain a reasonable gap and speed. The initial starting distance between the two cars was mentioned to each of the participants to be 30 meters. They were requested to keep a safe speed of 50 km/h (the lead car was driving within a range of 50 to 60 km/h). While driving behind the lead vehicle, they had to use the mobile phone attached inside the cockpit and interact with it depending on the activity that popped-up on the screen.

Driving environments set-up

For the simulator environment, we used OpenDS (version 2.5) [2] as 3D engine and the DriveLab platform Louveton et al. (2013) for triggering events and synchronising data. The test track used in the virtual environment was developed to mimic the geometry of the real test track, that has been used for the real driving condition.

For achieving this we have followed the procedure described in Avanesov et al. (2012): the real track geometry has been extracted from OpenStreetMap using OSM2World [3] and Blender (version 2.49b) [4] in order to make it a 3D model for OpenDS. We used a low-cost simulation setup: the display was handled by a video-projector, and controls by a Logitech gaming set including a steering wheel and pedals. The simulated car had an automatic transmission.

For the real-world environment, participants were to drive a Renault Twizy (electric quad-cycle, no gear change). Telemetry was accessed through a additional smartphone application making use of the On Board Diagnostic (OBD) port of the Renault Twizy and with the help of an OBD2 Bluetooth device.

Secondary task

The secondary task was displayed on a smartphone located on the right side of the driver (i.e., steering wheel assumed to be on the left-side of the cockpit). The smartphone used was a Galaxy S III mini running Android 4.1 with a 4 inches display size. The secondary task is implemented using generic

[2] http://opends.de/
[3] http://osm2world.org/
[4] http://www.blender.org/

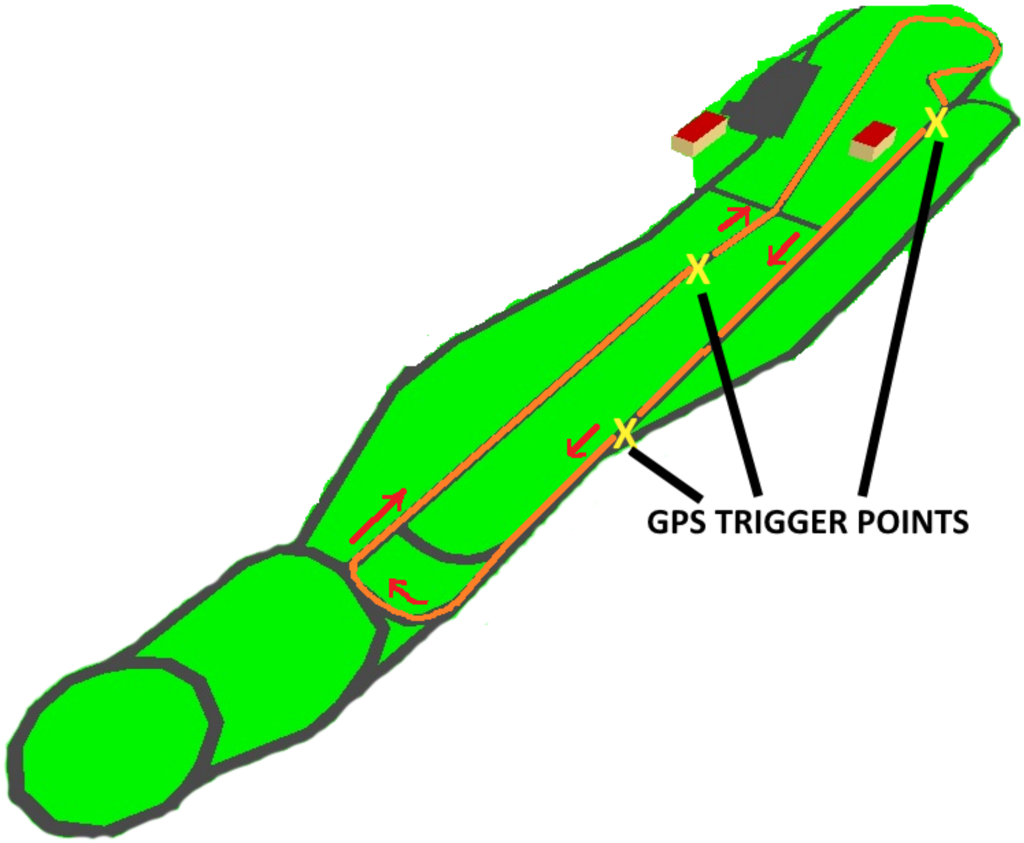

Figure 1: Schema of the test track used in both driving environment conditions. The three triggers for secondary events are indicated (yellow crosses) as well as the path of circulation (arrows).

Android widgets as they represent a realistic source of visual-manual distraction while driving.

The task displayed by the smartphone was a simple mental calculus challenge (i.e., of the type $5 \times 2 + 3 = ?$), then the user had to input the correct answer from a list of alternatives. This task was presented using five different types of interfaces: (i) Touch Button, (ii) Circular Dial, (iii) Input Data, (iv) Drop Down Menu, and (v) Radio Button (see Figure 2). Each trial was preceded by a visual and auditory notification then the secondary task was presented to the participant.

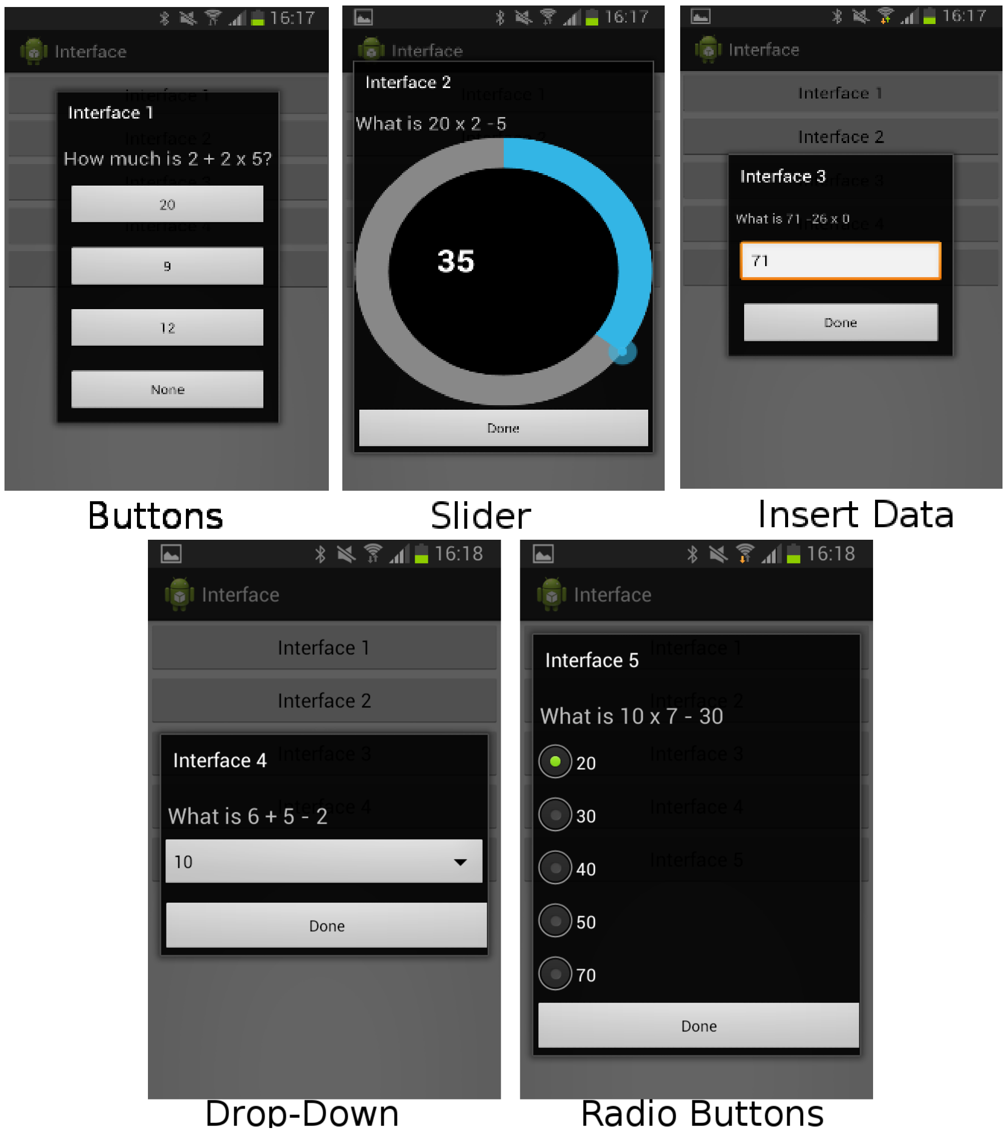

Figure 2: The five graphical user-interfaces used in the study. We used generic Android widgets as they represent realistic sources of distraction.

Brain-Computer Interface

The BCI device used to measure the brain signals was a MindCap XL headband equipped with a NeuroSky sensor [5]. This device measures brain activ-

[5]http://neurosky.com/

ity from sensors placed on the forehead and the proprietary algorithm automatically outputs the so-called attention level metric. Because the sensors are located on the forehead of the user, the attention level metric is supposed to be associated to focused attention and mental workload Norman (2013).

Experimental procedure

Participants were asked to drive on the test track for seven laps (lasting approximately 20-25 minutes). Prior to setting off the participants were instructed about the driving tasks. Each participant was given a chance to familiarise her/himself with the track by driving around it prior to starting the study, no data was recorded during the familiarisation phase.

The participants were instructed to keep an eye on the mobile phone attached to the cockpit and interact with it while continuing to drive. The secondary task and each of the interface options were explained to them. At the beginning of the experiment, the BCI device was attached to the forehead of the participant before initialising the smartphone application and the driving simulator environment.

The secondary task application was triggered on three fixed points located on the test track (cf. Figure 1). Thus, each participant had to perform 21 trials (three triggers on seven laps). The three points were located on a straight stretch of the track. Geo-fencing has been used with GPS coordinates in order to trigger trials in the real-world experiment while those coordinate have been translated in in the simulated environment Avanesov et al. (2012). Participants had until the prompt for the next task to answer the current one.

Experimental design and data analysis

We used a mixed factorial design with *Environment* (simulator or real driving) as a between-subject factor and user-interface styles, so-called *UI* as a within-subjects one. For each secondary task trial, the type of user-interface and the question/answer pair were selected at random.

For both simulated and real driving environments, the current speed of the car was collected. The secondary task usage was measured in terms of task completion time and success rate. Finally, we collected from the BCI device a metric called attention level. This metric is computed by the BCI using real-time measurements and a proprietary algorithm. The attention level metric was output every one second and was ranging from 0 to 100.

All the different types of data were synchronised and averaged across experimental conditions. We did not include a baseline condition in statistical analysis: Indeed, because of the test-track characteristics it seemed arbitrary to compare driving-only data samples with dual-task ones.

Parametric tests were used whenever the validity conditions were met, otherwise, non-parametric tests were used. Post-hoc tests were performed using pair-wise two-sample tests with a Bonferronni correction.

Results

Success and completion time

Overall, results show that participants were successful in achieving the secondary task, both in simulated (86%) and real environment (90%). The highest success rate was achieved with the RadioButton (99%) and DropDown Menu (97%), followed by the Slider (87%), Text Insertion (80%) and Button (76%). Those results indicate that participants performed reasonably well with all the user-interfaces proposed.

We performed a two-way mixed-design ANOVA on the completion time measurement. This analysis did not reveal an effect of the *Environment* factor (p = .17) or of the $Environment \times UI$ interaction (p = .86). However, the analysis revealed an effect resulting from the UI factor ($F(4, 91) = 30; p <$ .001).

On average the duration required for completing the tasks was higher for the real driving environment (16.3, sd = 17.9) than in for the simulated one (12.4, sd = 12.9). The most important variations were due to the type of interface (see also Figure 3): the post-hoc analysis revealed significant differences ($ps < .05$) when comparing Button condition ($8.2, sd = 7.6$) to DropDown ($14.1, sd = 14.6$), InsertData ($17.1, sd = 18.6$), and Slider ($17.8, sd = 14.3$) conditions. Finally, we found that Button and RadioButton ($11.8, sd = 15.7$) conditions did not differ significantly and were the interfaces which allowed for the fastest completion time.

Driving speed

The analysis evidenced an effect of the *Environment* factor ($F(1, 15) = 626.16; p < .001$) and of the UI one ($F(4, 89) = 2.97; p < .05$). We did not find an effect of $Environment \times UI$ interaction (p = .17).

While interacting with the smartphone, participants clearly drove at slower

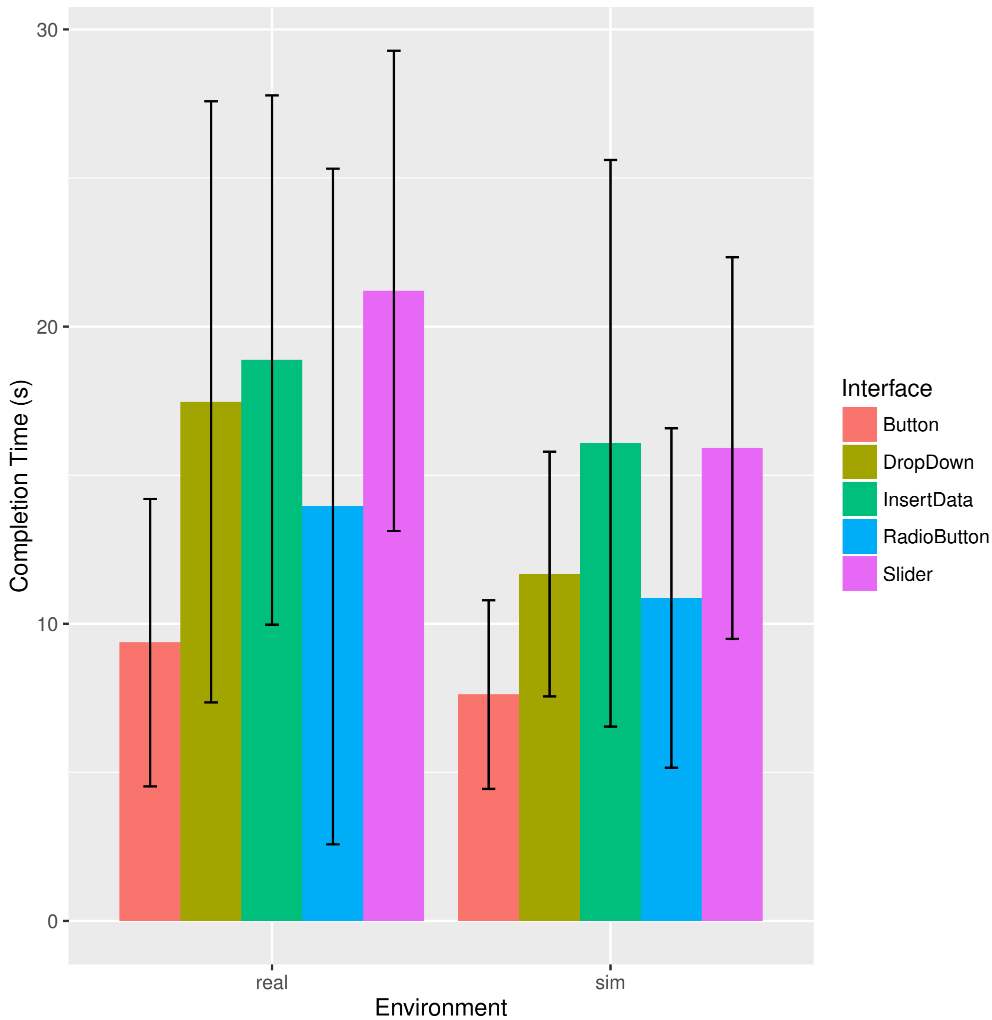

Figure 3: Completion time (represented with standard deviation) was relatively stable across environment conditions, although it varied noticeably for the different user-interfaces.

speed when immersed in a real driving environment ($26 km/h, sd = 5.8$) compared to when they were in a simulated one ($54.6 km/h, sd = 9.9$). The interface conditions also impacted the driving speed (cf. Figure 4): speed was the highest in the Button condition ($48.3 km/h, sd = 17.5$) followed by

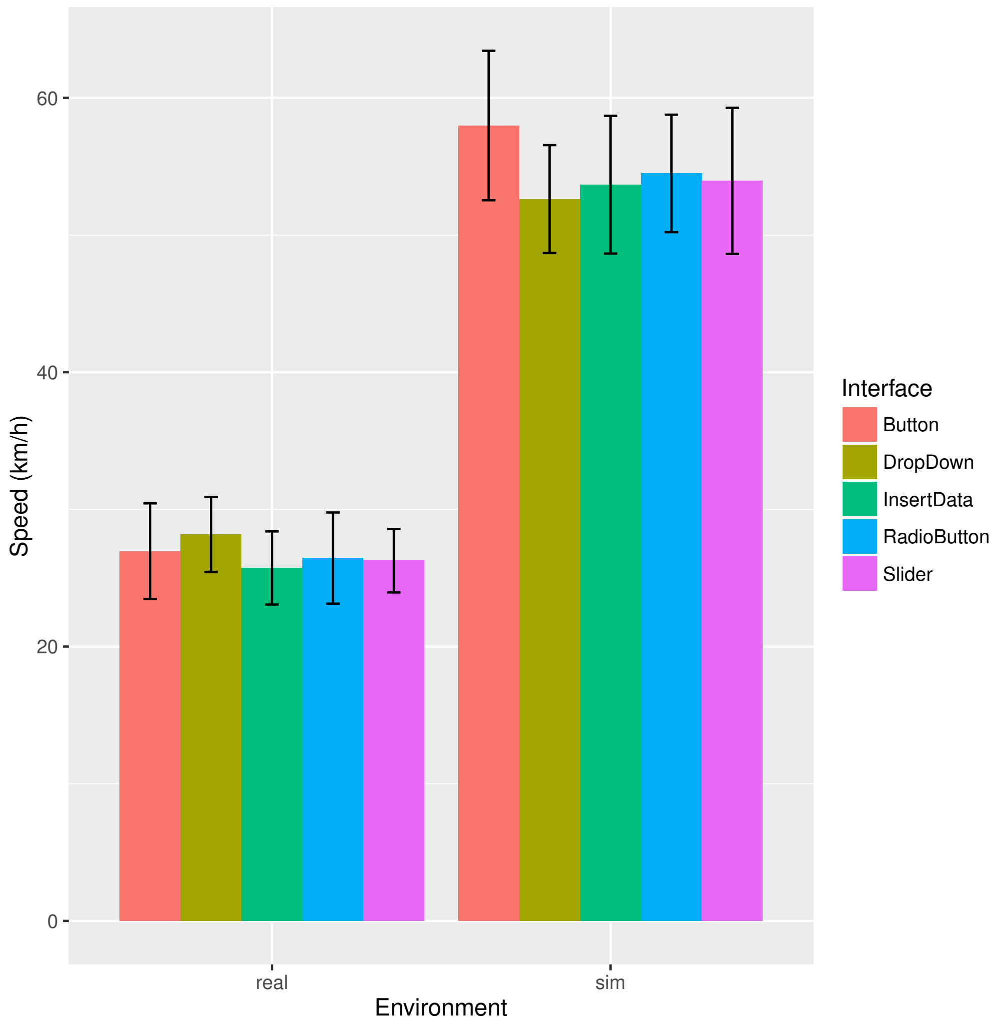

Figure 4: When dual-tasking, participants drove at a much slower speed in the real environment than in the simulated one. Practically no differences are found between the different user-interfaces. Speed is represented with standard deviation.

RadioButton ($46.8 km/h$, sd = 14.9), Slider ($45 km/h$, sd = 15.9), InsertData ($43.9 km/h$, sd = 15.3), and DropDown ($42.8 km/h$, sd = 13.9) conditions. However, the post-hoc analysis with corrected p-values failed to find significant differences between these conditions.

Attention metric

The analysis revealed an effect of the *Environment* factor ($F(1, 15) = 28.7$; $p < .001$) and an effect of the *Environment* $\times$ UI interaction ($F(4, 91) = 2.6$; $p < .05$). We found no effect of the UI factor ($p = .23$).

Results showed (see also Figure 5) that attention metric level was higher in the real driving environment (47, $sd = 17.7$) than in the simulated one (34, $sd = 12$). Also, the attention metric varied more across interface styles in the real environment (ranging from 42.6 to 51.6) than in the simulated one (ranging from 33.9 to 34.9).

Using a post-hoc analysis, more specific differences between user-interface styles have been found when comparing real and simulated driving environments. For instance, the DropDown interface in the real environment was associated ($p < .001$) with higher attention level (52.9, $sd = 15.9$) than Button (35.3, $sd = 10.2$), DropDown (35.5, $sd = 8.7$), InsertData (35.5, $sd = 8.9$), RadioButton (33.9, $sd = 8.7$) and Slider (33.2, $sd = 8.9$) interfaces in the simulated one.

We also found ($p < .05$) that the RadioButton interface in the real driving environment was associated with higher attention level (55.5, $sd = 16$) than the DropDown (35.5, $sd = 8.7$), InsertData (35.5, $sd = 8.9$) and RadioButton (33.9, $sd = 8.7$) interfaces in the simulated one.

Discussion

In this work we assessed the sensitivity of a commercial, affordable and easy-to-use BCI device in order to estimate the impact on driver distraction of different interface styles for a smartphone application in both a low-fidelity and real-driving environments.

Our results point to estimated workload being significantly higher in the real-driving environment than in the simulator one. This results actually confirms former findings Engström et al. (2005), although we used a much simpler physiological estimation of workload. Indeed, these authors used skin conductance and electrocardiogram which are highly specialised measurement devices. Because the BCI device we used implements a proprietary algorithm it is difficult to know to which cognitive process the so-called attention level metric actually refers to. However, taken together with Engström et al. (2005) our results are compatible with a correlation between

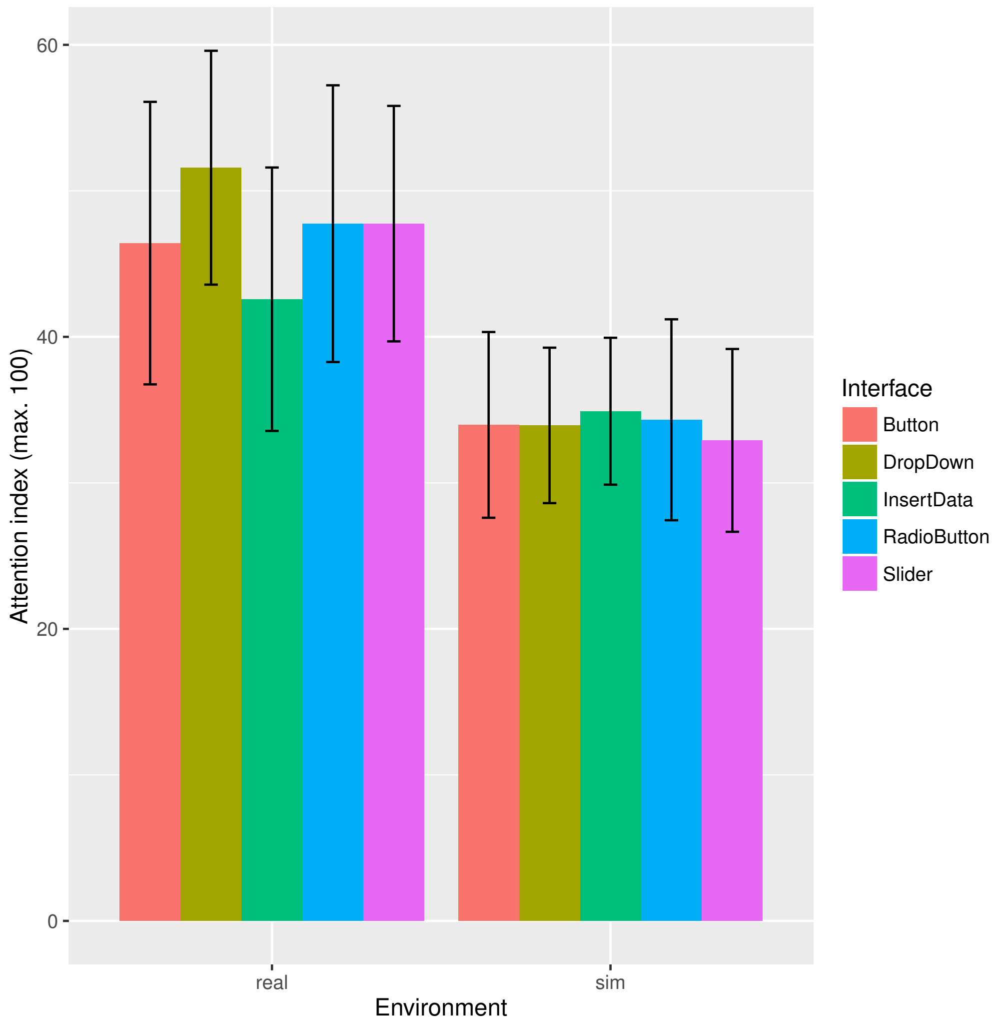

Figure 5: Attention metric (represented with standard deviation) was much higher in the real environment condition than in the simulated one. The variability of this metric was also higher between the different user-interfaces in the real compared to the simulated environment.

the attention level metric obtained from the MindCapXL and the increase of mental workload induced by the real-driving environment.

As expected by Jamson and Jamson (2010) completion time of the secondary task was consistent across driving environment while it was sensitive to the different user-interface styles. Those results suggest that this metric is a good indicator of secondary task difficulty independently of the environment. Contrary to Panerai et al. (2001), we did not find speed control metric to be stable across the two environments: Instead, driving speed was significantly lower in the real-driving condition.

Finally, completion time indicated that the two worst interfaces were the text-entry and slider widget which is congruent with earlier findings Kujala et al. (2013); Louveton et al. (2016). Speed control and attention level were not sensitive to the different widgets. Although, the attention level metric was shown as more variable in the real-driving condition indicating a possible interaction between the two factors. As said above, the BCI metric used is difficult to match with a specific cognitive process. One possible explanation is that the secondary task proposed was inducing visual-manual distraction more than cognitive distraction. Considering this and the location of the BCI sensors we can assume that the BCI device we used would have been more sensitive with cognitively more demanding tasks.

Conclusion

In this work, we assessed the sensitiveness of a commercial BCI device as an easy and affordable tool for estimating driver's mental workload. We used two driving environments (simulated and real) and a range of mainstream smartphone widgets as a test-bed for our measurements. Results showed that even if the device failed to distinguish between the different smartphone widgets, it demonstrate a sensitivity to the complexity and realism of the driving environment. We conclude that this type of device could be useful when assessing mental workload associated to different situations, although other techniques should be preferred in order to analyse specific distraction sources (e.g., those induced by different visual-manual interfaces).

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